UNITED STATES PATENT AND TRADEMARK OFFICE

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EXAMINER
PARK, EDWARD

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NOTIFICATION DATE	DELIVERY MODE
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Please find below and/or attached an Office communication concerning this application or proceeding.

The time period for reply, if any, is set in the attached communication.

Notice of the Office communication was sent electronically on above-indicated "Notification Date" to the following e-mail address(es):

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PTOL-90A (Rev. 04/07)

	Application No.	Applicant(s)
Office Action Summary	10/517,615	SUZUKI ET AL.
	Examiner	Art Unit	
	EDWARD PARK	2624	

-- The MAILING DATE of this communication appears on the cover sheet with the correspondence address --

Period for Reply

A SHORTENED STATUTORY PERIOD FOR REPLY IS SET TO EXPIRE _3_ MONTH(S) OR THIRTY (30) DAYS, WHICHEVER IS LONGER, FROM THE MAILING DATE OF THIS COMMUNICATION.

- Extensions of time may be available under the provisions of 37 CFR 1.136(a). In no event, however, may a reply be timely filed after SIX (6) MONTHS from the mailing date of this communication.
- If NO period for reply is specified above, the maximum statutory period will apply and will expire SIX (6) MONTHS from the mailing date of this communication.
- Failure to reply within the set or extended period for reply will, by statute, cause the application to become ABANDONED (35 U.S.C. § 133). Any reply received by the Office later than three months after the mailing date of this communication, even if timely filed, may reduce any earned patent term adjustment. See 37 CFR 1.704(b).

Status

1) ☒ Responsive to communication(s) filed on _6/3/08_.

2a) ☒ This action is **FINAL**.   2b) ☐ This action is non-final.

3) ☐ Since this application is in condition for allowance except for formal matters, prosecution as to the merits is closed in accordance with the practice under *Ex parte Quayle*, 1935 C.D. 11, 453 O.G. 213.

Disposition of Claims

4) ☒ Claim(s) _1-21_ is/are pending in the application.

    4a) Of the above claim(s) _____ is/are withdrawn from consideration.

5) ☐ Claim(s) _____ is/are allowed.

6) ☒ Claim(s) _1-21_ is/are rejected.

7) ☐ Claim(s) _____ is/are objected to.

8) ☐ Claim(s) _____ are subject to restriction and/or election requirement.

Application Papers

9) ☒ The specification is objected to by the Examiner.

10) ☐ The drawing(s) filed on _____ is/are: a) ☐ accepted or b) ☐ objected to by the Examiner.

    Applicant may not request that any objection to the drawing(s) be held in abeyance. See 37 CFR 1.85(a).

    Replacement drawing sheet(s) including the correction is required if the drawing(s) is objected to. See 37 CFR 1.121(d).

11) ☐ The oath or declaration is objected to by the Examiner. Note the attached Office Action or form PTO-152.

Priority under 35 U.S.C. § 119

12) ☒ Acknowledgment is made of a claim for foreign priority under 35 U.S.C. § 119(a)-(d) or (f).

    a) ☐ All   b) ☐ Some * c) ☐ None of:

      1. ☐ Certified copies of the priority documents have been received.

      2. ☐ Certified copies of the priority documents have been received in Application No. _____.

      3. ☒ Copies of the certified copies of the priority documents have been received in this National Stage application from the International Bureau (PCT Rule 17.2(a)).

    * See the attached detailed Office action for a list of the certified copies not received.

Attachment(s)

1) ☒ Notice of References Cited (PTO-892)
2) ☐ Notice of Draftsperson's Patent Drawing Review (PTO-948)
3) ☐ Information Disclosure Statement(s) (PTO/SB/08)
    Paper No(s)/Mail Date _____.

4) ☐ Interview Summary (PTO-413)
    Paper No(s)/Mail Date. _____ .
5) ☐ Notice of Informal Patent Application
6) ☐ Other: _____.

DETAILED ACTION

Specification

1.   The title of the invention is not descriptive. A new title is required that is clearly

indicative of the invention to which the claims are directed.

Claim Objections

2.   In response to applicant's amendment of claim 15, the previous claim objection is

withdrawn.

Claim Rejections - 35 USC § 103

3.   The following is a quotation of 35 U.S.C. 103(a) which forms the basis for all

obviousness rejections set forth in this Office action:

> (a) A patent may not be obtained though the invention is not identically disclosed or
> described as set forth in section 102 of this title, if the differences between the subject
> matter sought to be patented and the prior art are such that the subject matter as a whole
> would have been obvious at the time the invention was made to a person having ordinary
> skill in the art to which said subject matter pertains. Patentability shall not be negatived
> by the manner in which the invention was made.

4.   **Claims 1-4, 8, 20** are rejected under 35 U.S.C. 103(a) as being unpatentable over Schmid

et al ("Local Grayvalue Invariants for Image Retrieval", IEEE) with Roehrig et al (US

5,815,591), and further in view of Matsuzaki et al (US 6,804,683 B1).

Regarding **claim 1**, Schmid discloses an image recognition method which compares an

object image containing a plurality of objects with a model image containing a model to be

detected and extracts the model from the object image, the method comprising:

feature point extracting method for extracting a feature point from each of the object image and

the model image (see section 1.2, 2, 4.2 , interest points are local features with high information

content ... database contains a set of models where each model Mk is defined by the vector of

invariants Vj calculated at the interest points of the model images)

feature quantity retention method for extracting and retaining each of the object image and the

model image (see section 1.2, 2, 4.2, 4.4; database contains a set of models, each model Mk is

defined by the vectors of invariants calculated at the interest points of the model images; during

the storage process, each vector is added to the database; during recognition consists of finding

the model which corresponds to a given query image, that is the model which is most similar to

this image, for this image a set of vectors is computed which corresponds to the extracted interest

points and then compared);

feature quantity comparison method for comparing the feature quantity of each feature point of

the object image with the feature quantity of each feature point of the model image and

generating a candidate-associated feature point pair having similar feature quantities (see section

4.2, 4.2.1, recognition consists of finding the model Mk which corresponds to a given query

image , that is the model which is most similar to this image .. that produces a sum that is stored

in the vector T(k)); and

model attitude estimation method for detecting the presence or absence of the model on the

object image using the candidate-associated feature point pair and estimating a position and an

attitude of the model (see section 4.3 geometric constraint is added based on the angle between

neighbor points based on the transformation that can be locally approximated by a similarity

transformation which increases the score of the object to be recognized by having it be more

distinctive), if any, wherein the feature quantity comparison method itinerantly shifts one of the

feature points to be compared to find distances and generates the candidate-associated feature

point pair by assuming a shortest distance (see section 4.2, 4.2.1, 4.3, 4.4 semilocal constraints

are utilized so there is no miss-detection of points which has the p closest features are selected

which therefore transforms the vector T(k) which is determined by the distance threshold t

according to the X^2 distribution). Schmid does not disclose feature quantity retention means

for extracting and retaining, as a feature quantity, a density gradient direction histogram at least

acquired from density gradient information in a neighboring region at the feature point, the

density gradient direction histogram storing a number of points near the feature point having

each of a plurality of gradient directions. While Schmid discloses these steps, Schmid does not

disclose an apparatus implementing these steps.

Roehrig, in the same field of endeavor, teaches feature quantity retention means for

extracting and retaining, as a feature quantity, a density gradient direction histogram at least

acquired from density gradient information in a neighboring region at the feature point, the

density gradient direction histogram storing a number of points near the feature point having

each of a plurality of gradient directions (see col. 1, lines 60-67, col. 2, lines 1-40; central point or region, a histogram of gradient directions is centered around the candidate point).

It would have been obvious at the time the invention was made to one of ordinary skill in the art to modify Schmid reference to utilize density gradient direction histogram and to incorporate the density gradient direction histogram in comparing to candidate-associated feature point pair as taught by Roehrig, to detect and match certain previously stored images or data with high speed, high precision, and high accuracy (see col. 1, lines 40-59).

Matsuzami, in the same field of endeavor, teaches an apparatus implementing these steps (see figure 2 numeral 2, similar image retrieving engine).

It would have been obvious at the time the invention was made to one of ordinary skill in the art to modify the steps of Schmid with Roehrig combination to utilize an apparatus as taught by Matsuzami, in order to ensure a high computational speed, and to provide the ability to isolate and extract model images to be disseminated and used by the millions of people who have access to computers.

Regarding **claims 2-4**, Schmid further discloses extracts and retains, as the feature quantity, an average density gradient vector for each of plurality of partial regions into which the neighboring region is further divided (see section 3.1, V represent the average luminance), and the feature quantity comparison means generates the candidate-associated feature point pair based on a distance between density gradient direction histograms for the feature points to be compared and on similarity between feature vectors which are collected in the neighboring region as average density gradient vectors in each of the partial regions (see section 4.2, 4.2.1, 4.3, 4.4 semilocal constraints are utilized so there is no miss-detection of points which has the p

closest features are selected which therefore transforms the vector T(k) which is determined by the distance threshold t according to the X^2 distribution);

generates a provisional candidate-associated feature point pair based on a distance between the density gradient direction histograms for the feature points to be compared and, based on the similarity between feature vectors, selects the candidate-associated feature point pair from the provisional candidate-associated feature point pair (see section 4.2, 4.3 essentially the provisional candidate implies repeating the process which is evident in any algorithm);

using a rotation angle equivalent to a shift a amount giving the shortest distance to correct a density gradient direction of a density gradient vector in the neighboring region and selects the candidate-associated feature point pair from the provisional candidate-associated feature point pair based on similarity between the feature vectors in a corrected neighboring region (see figures 4, 5, section 4.3 geometric constraint is added based on the angel between neighbor points).

Regarding **claim 8**, Schmid further discloses candidate-associated feature point pair selection means for creating a rotation angle histogram concerning a rotation angle equivalent to a shift amount giving the shortest distance and selects a candidate-associated feature point pair giving a rotation angle for a peak in the rotation angle histogram from the candidate-associated feature point pair generated by the feature quantity comparison means (see figures 4, 5, section 4.3 geometric constraint is added based on the angel between neighbor points), wherein the model attitude estimation means detects the presence or absence of the model on the object image using a candidate-associated feature point pair selected by the candidate-associated feature point pair selection means and estimates a position and an attitude of the model, if any (see

section 4.3 geometric constraint is added based on the angle between neighbor points based on

the transformation that can be locally approximated by a similarity transformation which

increases the score of the object to be recognized by having it be more distinctive).

Regarding **claim 20**, Schmid discloses an image recognition method which compares an

object image containing a plurality of objects with a model image containing a model to be

detected and extracts the model from the object image, the method comprising:

a feature point extracting method configure to extract a feature point from each of the object

image and the model image (see section 1.2, 2, 4.2, interest points are local features with high

information content … database contains a set of models where each model Mk is defined by the

vector of invariants Vj calculated at the interest points of the model images)

a feature quantity retention method configured to extract and retain each of the object image and

the model image (see section 1.2, 2, 4.2, 4.4; database contains a set of models, each model Mk

is defined by the vectors of invariants calculated at the interest points of the model images;

during the storage process, each vector is added to the database; during recognition consists of

finding the model which corresponds to a given query image, that is the model which is most

similar to this image, for this image a set of vectors is computed which corresponds to the

extracted interest points and then compared);

a feature quantity comparison method configured to compare the feature quantity of each feature

point of the object image with the feature quantity of each feature point of the model image and

generating a candidate-associated feature point pair having similar feature quantities (see section

4.2, 4.2.1, recognition consists of finding the model Mk which corresponds to a given query

image , that is the model which is most similar to this image .. that produces a sum that is stored

in the vector T(k)); and

a model attitude estimation method configured to detect the presence or absence of the model on

the object image using the candidate-associated feature point pair and estimating a position and

an attitude of the model (see section 4.3 geometric constraint is added based on the angle

between neighbor points based on the transformation that can be locally approximated by a

similarity transformation which increases the score of the object to be recognized by having it be

more distinctive), if any, wherein the feature quantity comparison method itinerantly shifts one

of the feature points to be compared to find distances and generates the candidate-associated

feature point pair by assuming a shortest distance (see section 4.2, 4.2.1, 4.3, 4.4 semilocal

constraints are utilized so there is no miss-detection of points which has the p closest features are

selected which therefore transforms the vector T(k) which is determined by the distance

threshold t according to the X^2 distribution). Schmid does not disclose extracting and retaining,

as a feature quantity, a density gradient direction histogram at least acquired from density

gradient information in a neighboring region at the feature point, the density gradient direction

histogram storing a number of points near the feature point having each of a plurality of gradient

directions. While Schmid discloses these steps, Schmid does not disclose an apparatus

implementing these steps.

Roehrig, in the same field of endeavor, teaches extracting and retaining, as a feature

quantity, a density gradient direction histogram at least acquired from density gradient

information in a neighboring region at the feature point, the density gradient direction histogram

storing a number of points near the feature point having each of a plurality of gradient directions

(see col. 1, lines 60-67, col. 2, lines 1-40; central point or region, a histogram of gradient

directions is centered around the candidate point).

It would have been obvious at the time the invention was made to one of ordinary skill in

the art to modify Schmid reference to utilize density gradient direction histogram and to

incorporate the density gradient direction histogram in comparing to candidate-associated feature

point pair as taught by Roehrig, to detect and match certain previously stored images or data with

high speed, high precision, and high accuracy (see col. 1, lines 40-59).

Matsuzami, in the same field of endeavor, teaches an apparatus implementing these steps

(see figure 2 numeral 2, similar image retrieving engine).

It would have been obvious at the time the invention was made to one of ordinary skill in

the art to modify the steps of Schmid with Roehrig combination to utilize an apparatus as taught

by Matsuzami, in order to ensure a high computational speed, and to provide the ability to isolate

and extract model images to be disseminated and used by the millions of people who have access

to computers.

5.   **Claims 5-7, 9, 10** are rejected under 35 U.S.C. 103(a) as being unpatentable over Schmid

et al ("Local Grayvalue Invariants for Image Retrieval", IEEE), Roehrig et al (US 5,815,591)

with Matsuzaki et al (US 6,804,683 B1), and further in view of Lowe ("Object Recognition from

Local Scale-Invariant Features", Computer Vision).

Regarding **claim 5-7,** Schmid, Roehrig with Matsuzaki combination discloses all

elements as mentioned above in claim 1. Schmid, Roehrig with Matsuzaki combination does not

disclose projecting an affine transformation parameter determined from three randomly selected

candidate-associated feature point pairs onto a parameter space and finds an affine

transformation parameter to determine a position and an attitude of the model based on an affine

transformation parameter belonging to a cluster having the largest number of members out of

clusters formed on a parameter space, a centroid for the cluster having the largest number of

members to be an affine transformation parameter to determine a position and an attitude of the

model, and a least squares estimation to find an affine transformation parameter for determining

a position and attitude of the model.

Lowe teaches projecting an affine transformation parameter determined from three

randomly selected candidate-associated feature point pairs onto a parameter space (see section 1

scale-invariant features are efficiently identified by using a staged filter approach .. the features

achieve partial invariance to local variations using affine or 3D projections by blurring the image

gradient locations .. when at least 3 keys agree on the model parameters with low residual) and

finds an affine transformation parameter to determine a position and an attitude of the model

based on an affine transformation parameter belonging to a cluster having the largest number of

members out of clusters formed on a parameter space (see sections 3, 6, 9 solve for the affine

transformation parameters … select key locations at maxima and minima of a difference of

Gaussian function applied in scale space), a centroid for the cluster having the largest number of

members to be an affine transformation parameter to determine a position and an attitude of the

model (see section 5, cluster reliable model hypotheses is to use the Hough transform to search

for keys that agree upon a particular model pose where each model key in the database contains a

record of the key's parameters relative to the model coordinate system and therefore can predict

the model location), and a least squares estimation to find an affine transformation parameter for

determining a position and attitude of the model (see section 1, collection of keys that agree on a

potential model pose are identified and then through a least-squares fit to a final estimate of model parameters).

It would have been obvious at the time the invention was made to one of ordinary skill in the art to modify Schmid, Roehrig with Matsuzaki combination to utilize affine transformation parameter with centroid and least squares estimation as taught by Lowe, to "allow for more accurate verification and pose determination than in approaches that rely only on indexing" (see section 9).

Regarding **claim 9 and 10**, Schmid, Roehrig with Matsuzaki combination discloses all elements as mentioned above in claim 1. Schmid, Roehrig with Matsuzaki combination does not disclose a candidate associated feature point pair selection means for performing generalized Hough transform for a candidate-associated feature point pair generated by the feature quantity comparison means, assuming a rotation angle, enlargement and reduction ratios, and horizontal and vertical linear displacements to be a parameter space, and selecting a candidate-associated feature point pair having voted for the most voted parameter from candidate-associated feature point pairs generated by the feature quantity comparison means,
wherein the model attitude estimation means detects the presence or absence of the model on the object image using a candidate-associated feature point pair selected by the candidate-associated feature point pair selection means and estimates a position and an attitude of the model, if any; and extracting a local maximum point or a local minimum point in second-order differential filter output images with respective resolutions as the feature point, i.e., a point free from positional changes due to resolution changes within a specified range in a multi-resolution pyramid

structure acquired by repeatedly applying smoothing filtering and reduction resampling to the object image or the model image.

Lowe, in the same field of endeavor, teaches a candidate associated feature point pair selection means for performing generalized Hough transform for a candidate-associated feature point pair generated by the feature quantity comparison means, assuming a rotation angle, enlargement and reduction ratios, and horizontal and vertical linear displacements to be a parameter space, and selecting a candidate-associated feature point pair having voted for the most voted parameter from candidate-associated feature point pairs generated by the feature quantity comparison means (see section 5, 6 Hough transform to search for keys that agree upon a particular model pose … affine rotation, scale, and stretch)

wherein the model attitude estimation means detects the presence or absence of the model on the object image using a candidate-associated feature point pair selected by the candidate-associated feature point pair selection means and estimates a position and an attitude of the model, if any (see section 5-7 closest match to the correct corresponding key in the second image); and extracting a local maximum point or a local minimum point in second-order differential filter output images with respective resolutions as the feature point, i.e., a point free from positional changes due to resolution changes within a specified range in a multi-resolution pyramid structure acquired by repeatedly applying smoothing filtering and reduction resampling to the object image or the model image (see section 1 and 3, 3.1, staged filtering approach … maxima or minima of a difference of Gaussian function by building an image pyramid with resampling between each level … Gaussian kernel and its derivates are the only possible smoothing kernels for scale space analysis).

It would have been obvious at the time the invention was made to one of ordinary skill in the art to modify Schmid, Roehrig with Matsuzaki combination to utilize a candidate-associated feature point pair and second-order differential filter as taught by Lowe, to "allow for more accurate verification and pose determination than in approaches that rely only on indexing" (see section 9).

6.   **Claims 11-15, 21** are rejected under 35 U.S.C. 103(a) as being unpatentable over Schmid et al ("Local Grayvalue Invariants for Image Retrieval", IEEE), Roehrig et al (US 5,815,591) with Lowe ("Object Recognition from Local Scale-Invariant Features", Computer Vision), and further in view of Matsuzaki et al (US 6,804,683 B1).

Regarding **claims 11-13**, Schmid discloses an image recognition method which compares an object image containing a plurality of objects with a model image containing a model to be detected and extracts the model from the object image, the apparatus comprising:
a feature point extracting step of extracting a feature point from each of the object image and the model image (see section 1.2, 2, 4.2, interest points are local features with high information content … database contains a set of models where each model Mk is defined by the vector of invariants Vj calculated at the interest points of the model images)
a feature quantity retention step of extracting and retaining each of the object image and the model image (see section 1.2, 2, 4.2, 4.4; database contains a set of models, each model Mk is defined by the vectors of invariants calculated at the interest points of the model images; during the storage process, each vector is added to the database; during recognition consists of finding the model which corresponds to a given query image, that is the model which is most similar to

this image, for this image a set of vectors is computed which corresponds to the extracted interest

points and then compared);

a feature quantity comparison step of comparing the feature quantity of each feature point of the

object image with the feature quantity of each feature point of the model image and generating a

candidate-associated feature point pair having similar feature quantities (see section 4.2, 4.2.1,

recognition consists of finding the model Mk which corresponds to a given query image, that is

the model which is most similar to this image .. that produces a sum that is stored in the vector

T(k));

a model attitude estimation step of detecting the presence or absence of the model on the object

image using the candidate-associated feature point pair and estimating a position and an attitude

of the model (see section 4.3 geometric constraint is added based on the angle between neighbor

points based on the transformation that can be locally approximated by a similarity

transformation which increases the score of the object to be recognized by having it be more

distinctive).

Schmid does not teach extracting and retaining a feature quantity in a neighboring region

at the feature point, the feature quantity being a density direction histogram storing an umber of

points near the feature point having each of a plurality of gradient directions, projecting an affine

transformation parameter determined from three randomly selected candidate-associated feature

point pairs onto a parameter space and finds an affine transformation parameter to determine a

position and an attitude of the model based on an affine transformation parameter belonging to a

cluster having the largest number of members out of clusters formed on a parameter space, a

centroid for the cluster having the largest number of members to be an affine transformation

parameter to determine a position and an attitude of the model, and a least squares estimation to find an affine transformation parameter for determining a position and attitude of the model.

Roehrig, in the same field of endeavor, teaches extracting and retaining a feature quantity in a neighboring region at the feature point, the feature quantity being a density direction histogram storing an umber of points near the feature point having each of a plurality of gradient directions (see col. 1, lines 60-67, col. 2, lines 1-40; central point or region, a histogram of gradient directions is centered around the candidate point).

It would have been obvious at the time the invention was made to one of ordinary skill in the art to modify Schmid reference to utilize density gradient direction histogram and to incorporate the density gradient direction histogram in comparing to candidate-associated feature point pair as taught by Roehrig, to detect and match certain previously stored images or data with high speed, high precision, and high accuracy (see col. 1, lines 40-59).

Lowe teaches projecting an affine transformation parameter determined from three randomly selected candidate-associated feature point pairs onto a parameter space (see section 1 scale-invariant features are efficiently identified by using a staged filter approach .. the features achieve partial invariance to local variations using affine or 3D projections by blurring the image gradient locations .. when at least 3 keys agree on the model parameters with low residual) and finds an affine transformation parameter to determine a position and an attitude of the model based on an affine transformation parameter belonging to a cluster having the largest number of members out of clusters formed on a parameter space (see sections 3, 6, 9 solve for the affine transformation parameters … select key locations at maxima and minima of a difference of Gaussian function applied in scale space) and a centroid for the cluster having the largest number

of members to be an affine transformation parameter to determine a position and an attitude of

the model (see section 5, cluster reliable model hypotheses is to use the Hough transform to

search for keys that agree upon a particular model pose where each model key in the database

contains a record of the key's parameters relative to the model coordinate system and therefore

can predict the model location), and a least squares estimation to find an affine transformation

parameter for determining a position and attitude of the model (see section 1, collection of keys

that agree on a potential model pose are identified and then through a least-squares fit to a final

estimate of model parameters).

It would have been obvious at the time the invention was made to one of ordinary skill in

the art to modify Schmid with Roehrig combination to utilize affine transformation parameter

with centroid and least squares estimation as taught by Lowe, to "allow for more accurate

verification and pose determination than in approaches that rely only on indexing" (see section

9).

While Schmid discloses these steps, Schmid does not disclose an apparatus implementing

these steps.

Matsuzami, in the same field of endeavor, teaches an apparatus implementing these steps

(see figure 2 numeral 2, similar image retrieving engine).

It would have been obvious at the time the invention was made to one of ordinary skill in

the art to modify the steps of Schmid, Roehrig with Lowe combination to utilize an apparatus as

taught by Matsuzami, in order to ensure a high computational speed, and to provide the ability to

isolate and extract model images to be disseminated and used by the millions of people who have

access to computers.

Regarding **claims 14, 15**, Schmid, Roehrig, Lowe with Matsuzaki combination discloses all elements as mentioned above in claim 11. Schmid, Roehrig, Lowe with Matsuzaki combination does not disclose a candidate associated feature point pair selection means for performing generalized Hough transform for a candidate-associated feature point pair generated by the feature quantity comparison means, assuming a rotation angle, enlargement and reduction ratios, and horizontal and vertical linear displacements to be a parameter space, and selecting a candidate-associated feature point pair having voted for the most voted parameter from candidate-associated feature point pairs generated by the feature quantity comparison means, wherein the model attitude estimation means detects the presence or absence of the model on the object image using a candidate-associated feature point pair selected by the candidate-associated feature point pair selection means and estimates a position and an attitude of the model, if any; and extracting a local maximum point or a local minimum point in second-order differential filter output images with respective resolutions as the feature point, i.e., a point free from positional changes due to resolution changes within a specified range in a multi-resolution pyramid structure acquired by repeatedly applying smoothing filtering and reduction resampling to the object image or the model image.

Lowe, in the same field of endeavor, teaches a candidate associated feature point pair selection means for performing generalized Hough transform for a candidate-associated feature point pair generated by the feature quantity comparison means, assuming a rotation angle, enlargement and reduction ratios, and horizontal and vertical linear displacements to be a parameter space, and selecting a candidate-associated feature point pair having voted for the most voted parameter from candidate-associated feature point pairs generated by the feature

quantity comparison means (see section 5, 6 Hough transform to search for keys that agree upon

a particular model pose … affine rotation, scale, and stretch)

wherein the model attitude estimation means detects the presence or absence of the model on the

object image using a candidate-associated feature point pair selected by the candidate-associated

feature point pair selection means and estimates a position and an attitude of the model, if any

(see section 5-7 closest match to the correct corresponding key in the second image); and

extracting a local maximum point or a local minimum point in second-order differential filter

output images with respective resolutions as the feature point, i.e., a point free from positional

changes due to resolution changes within a specified range in a multi-resolution pyramid

structure acquired by repeatedly applying smoothing filtering and reduction resampling to the

object image or the model image (see section 1 and 3, 3.1, staged filtering approach … maxima

or minima of a difference of Gaussian function by building an image pyramid with resampling

between each level … Gaussian kernel and its derivates are the only possible smoothing kernels

for scale space analysis).

It would have been obvious at the time the invention was made to one of ordinary skill in

the art to modify Schmid, Roehrig, Lowe with Matsuzaki combination as mentioned above in

claim 11, to utilize a candidate-associated feature point pair and second-order differential filter as

taught by Lowe, to "allow for more accurate verification and pose determination than in

approaches that rely only on indexing" (see section 9).

Regarding **claim 21**, Schmid discloses an image recognition method which compares an

object image containing a plurality of objects with a model image containing a model to be

detected and extracts the model from the object image, the method comprising:

a feature point extracting step configured to extract a feature point from each of the object image

and the model image (see section 1.2, 2, 4.2 , interest points are local features with high

information content … database contains a set of models where each model Mk is defined by the

vector of invariants Vj calculated at the interest points of the model images)

a feature quantity retention step configured to extract and retain each of the object image and the

model image (see section 1.2, 2, 4.2, 4.4; database contains a set of models, each model Mk is

defined by the vectors of invariants calculated at the interest points of the model images; during

the storage process, each vector is added to the database; during recognition consists of finding

the model which corresponds to a given query image, that is the model which is most similar to

this image, for this image a set of vectors is computed which corresponds to the extracted interest

points and then compared);

a feature quantity comparison step configured to compare the feature quantity of each feature

point of the object image with the feature quantity of each feature point of the model image and

generating a candidate-associated feature point pair having similar feature quantities, each

feature quantity not including gradient magnitude information (see section 4.2, 4.2.1, recognition

consists of finding the model Mk which corresponds to a given query image , that is the model

which is most similar to this image .. that produces a sum that is stored in the vector T(k));

a model attitude estimation step configured to detect the presence or absence of the model on the

object image using the candidate-associated feature point pair and estimating a position and an

attitude of the model (see section 4.3 geometric constraint is added based on the angle between

neighbor points based on the transformation that can be locally approximated by a similarity

transformation which increases the score of the object to be recognized by having it be more distinctive).

Schmid does not teach extracting and retaining, as a feature quantity, a density gradient direction histogram at least acquired from density gradient information in a neighboring region at the feature point, the density gradient direction histogram storing a number of points near the feature point having each of a plurality of gradient directions; projecting an affine transformation parameter determined from three randomly selected candidate-associated feature point pairs onto a parameter space and finds an affine transformation parameter to determine a position and an attitude of the model based on an affine transformation parameter belonging to a cluster having the largest number of members out of clusters formed on a parameter space.

Roehrig, in the same field of endeavor, teaches extracting and retaining, as a feature quantity, a density gradient direction histogram at least acquired from density gradient information in a neighboring region at the feature point, the density gradient direction histogram storing a number of points near the feature point having each of a plurality of gradient directions (see col. 1, lines 60-67, col. 2, lines 1-40; central point or region, a histogram of gradient directions is centered around the candidate point).

It would have been obvious at the time the invention was made to one of ordinary skill in the art to modify Schmid reference to utilize density gradient direction histogram and to incorporate the density gradient direction histogram in comparing to candidate-associated feature point pair as taught by Roehrig, to detect and match certain previously stored images or data with high speed, high precision, and high accuracy (see col. 1, lines 40-59).

Lowe teaches projecting an affine transformation parameter determined from three randomly selected candidate-associated feature point pairs onto a parameter space (see section 1 scale-invariant features are efficiently identified by using a staged filter approach .. the features achieve partial invariance to local variations using affine or 3D projections by blurring the image gradient locations .. when at least 3 keys agree on the model parameters with low residual) and finds an affine transformation parameter to determine a position and an attitude of the model based on an affine transformation parameter belonging to a cluster having the largest number of members out of clusters formed on a parameter space (see sections 3, 6, 9 solve for the affine transformation parameters ... select key locations at maxima and minima of a difference of Gaussian function applied in scale space).

It would have been obvious at the time the invention was made to one of ordinary skill in the art to modify Schmid with Roehrig combination to utilize affine transformation parameter as taught by Lowe, to "allow for more accurate verification and pose determination than in approaches that rely only on indexing" (see section 9).

While Schmid discloses these steps, Schmid does not disclose an apparatus implementing these steps.

Matsuzami, in the same field of endeavor, teaches an apparatus implementing these steps (see figure 2 numeral 2, similar image retrieving engine).

It would have been obvious at the time the invention was made to one of ordinary skill in the art to modify the steps of Schmid, Roehrig with Lowe combination to utilize an apparatus as taught by Matsuzami, in order to ensure a high computational speed, and to provide the ability to

isolate and extract model images to be disseminated and used by the millions of people who have

access to computers.

7.   **Claim 16** is rejected under 35 U.S.C. 103(a) as being unpatentable over Schmid et al

("Local Grayvalue Invariants for Image Retrieval", IEEE) in view of Roehrig et al (US

5,815,591).

Regarding **claim 16**, Schmid discloses an image recognition method which compares an

object image containing a plurality of objects with a model image containing a model to be

detected and extracts the model from the object image, the method comprising:

extracting a feature point from each of the object image and the model image (see section 1.2, 2,

4.2, 4.4; database contains a set of models, each model Mk is defined by the vectors of invariants

calculated at the interest points of the model images; during the storage process, each vector is

added to the database; during recognition consists of finding the model which corresponds to a

given query image, that is the model which is most similar to this image, for this image a set of

vectors is computed which corresponds to the extracted interest points and then compared)

extracting and retaining each of the object image and the model image (see section 2, 4.4);

comparing the feature quantity of each feature point of the object image with the feature quantity

of each feature point of the model image and generating a candidate-associated feature point pair

having similar feature quantities (see section 4.2, 4.2.1, recognition consists of finding the model

Mk which corresponds to a given query image , that is the model which is most similar to this

image .. that produces a sum that is stored in the vector T(k)); and

detecting the presence or absence of the model on the object image using the candidate-

associated feature point pair and estimating a position and an attitude of the model (see section

4.3 geometric constraint is added based on the angle between neighbor points based on the

transformation that can be locally approximated by a similarity transformation which increases

the score of the object to be recognized by having it be more distinctive), if any,

wherein the comparing itinerantly shifts one of the feature points to be compared to find

distances and generates the candidate-associated feature point pair by assuming a shortest

distance (see section 4.2, 4.2.1, 4.3, 4.4 semilocal constraints are utilized so there is no miss-

detection of points which has the p closest features are selected which therefore transforms the

vector T(k) which is determined by the distance threshold t according to the X^2 distribution).

Schmid does not disclose extracting and retaining, as a feature quantity, a density gradient

direction histogram at least acquired from density gradient information in a neighboring region at

the feature point, the density gradient direction histogram storing a number of points near the

feature point having each of a plurality of gradient directions.

Roehrig, in the same field of endeavor, teaches extracting and retaining, as a feature

quantity, a density gradient direction histogram at least acquired from density gradient

information in a neighboring region at the feature point, the density gradient direction histogram

storing a number of points near the feature point having each of a plurality of gradient directions

(see col. 1, lines 60-67, col. 2, lines 1-40; central point or region, a histogram of gradient

directions is centered around the candidate point).

It would have been obvious at the time the invention was made to one of ordinary skill in

the art to modify Schmid reference to utilize density gradient direction histogram and to

incorporate the density gradient direction histogram in comparing to candidate-associated feature

point pair as taught by Roehrig, to detect and match certain previously stored images or data with high speed, high precision, and high accuracy (see col. 1, lines 40-59).

8.   **Claim 17** is rejected under 35 U.S.C. 103(a) as being unpatentable over Schmid et al ("Local Grayvalue Invariants for Image Retrieval", IEEE) with Roehrig et al (US 5,815,591), and further in view of Lowe ("Object Recognition from Local Scale-Invariant Features", Computer Vision).

Regarding **claim 17**, Schmid discloses an image recognition method which compares an object image containing a plurality of objects with a model image containing a model to be detected and extracts the model from the object image, the apparatus comprising:

extracting a feature point from each of the object image and the model image (see section 1.2, 2, 4.2, 4.4; database contains a set of models, each model Mk is defined by the vectors of invariants calculated at the interest points of the model images; during the storage process, each vector is added to the database; during recognition consists of finding the model which corresponds to a given query image, that is the model which is most similar to this image, for this image a set of vectors is computed which corresponds to the extracted interest points and then compared)

extracting and retaining each of the object image and the model image (see figure 3, section 4.2, 4.2.1, 4.2.2, voting algorithm which is a sum of the number of times each model is selected which produces a histogram that correctly identifies the model images from the database of images);

comparing the feature quantity of each feature point of the object image with the feature quantity of each feature point of the model image and generating a candidate-associated feature point pair having similar feature quantities (see section 4.2, 4.2.1, recognition consists of finding the model

Mk which corresponds to a given query image , that is the model which is most similar to this

image .. that produces a sum that is stored in the vector T(k)); and

detecting the presence or absence of the model on the object image using the candidate-

associated feature point pair and estimating a position and an attitude of the model (see section

4.3 geometric constraint is added based on the angle between neighbor points based on the

transformation that can be locally approximated by a similarity transformation which increases

the score of the object to be recognized by having it be more distinctive).

Schmid does not teach extracting and retaining a feature quantity in a neighboring region

a the feature point, the feature quantity being a density gradient direction histogram storing a

number of points near the feature point having each of a plurality of gradient directions;

projecting an affine transformation parameter determined from three randomly selected

candidate-associated feature point pairs onto a parameter space and finds an affine

transformation parameter to determine a position and an attitude of the model based on an affine

transformation parameter belonging to a cluster having the largest number of members out of

clusters formed on a parameter space.

Roehrig, in the same field of endeavor, teaches extracting and retaining a feature quantity

in a neighboring region a the feature point, the feature quantity being a density gradient direction

histogram storing a number of points near the feature point having each of a plurality of gradient

directions (see col. 1, lines 60-67, col. 2, lines 1-40; central point or region, a histogram of

gradient directions is centered around the candidate point).

It would have been obvious at the time the invention was made to one of ordinary skill in

the art to modify Schmid reference to utilize density gradient direction histogram and to

incorporate the density gradient direction histogram in comparing to candidate-associated feature point pair as taught by Roehrig, to detect and match certain previously stored images or data with high speed, high precision, and high accuracy (see col. 1, lines 40-59).

Lowe teaches projecting an affine transformation parameter determined from three randomly selected candidate-associated feature point pairs onto a parameter space (see section 1 scale-invariant features are efficiently identified by using a staged filter approach .. the features achieve partial invariance to local variations using affine or 3D projections by blurring the image gradient locations .. when at least 3 keys agree on the model parameters with low residual) and finds an affine transformation parameter to determine a position and an attitude of the model based on an affine transformation parameter belonging to a cluster having the largest number of members out of clusters formed on a parameter space (see sections 3, 6, 9 solve for the affine transformation parameters ... select key locations at maxima and minima of a difference of Gaussian function applied in scale space).

It would have been obvious at the time the invention was made to one of ordinary skill in the art to modify Schmid with Roehrig combination to utilize affine transformation parameter as taught by Lowe, to "allow for more accurate verification and pose determination than in approaches that rely only on indexing" (see section 9).

9.   **Claim 18** is rejected under 35 U.S.C. 103(a) as being unpatentable over Watanabe et al (US 7,084,900 B1) with Schmid et al ("Local Grayvalue Invariants for Image Retrieval", IEEE), and further in view of Roehrig et al (US 5,815,591).

Regarding **claim 18**, Watanabe discloses an autonomous robot apparatus (figure 1, col. 2, lines 37-60, wrist of a robot RB that is included in the robot system) capable of comparing an

input image with a model image containing a model to be detected and extracting the model from

the input image, the apparatus comprising:

    image input means for imaging an outside environment to generate the input image

(figure 1, numeral 20; col. 2, lines 37-60, image capturing device (camera or visual sensor) that

captures an image of a stack of workpieces); and a processor (figure 3, numeral 1; col. 3, lines 3-

10, robot operation programs that are performed by the processor).

    Watanabe does not disclose a feature point extracting method for extracting a feature

point from each of the input image and the model image;

    feature quantity retention method for extracting and retaining, as a feature quantity, a

density gradient direction histogram at least acquired from density gradient information in a

neighboring region at the feature point in each of the input image and the model image, the

density gradient direction histogram storing a number of points near the feature point having

each of a plurality of gradient directions;

    feature quantity comparison method for comparing the feature quantity of each feature

point of the input image with the feature quantity of each feature point of the model image and

generating a candidate-associated feature point pair having similar feature quantities; and

    model attitude estimation method for detecting the presence or absence of the model on

the input image using the candidate-associated feature point pair and estimating a position and an

attitude of the model, if any, wherein the feature quantity comparison method itinerantly shifts

one of the density gradient direction histograms of feature points to be compared in density

gradient direction to find distances between the density gradient direction histograms and

generates the candidate-associated feature point pair by assuming a shortest distance to be a

distance between the density gradient direction histograms.

Schmid, in the same field of endeavor, teaches a feature point extracting method for

extracting a feature point from each of the input image and the model image (see section 1.2, 2,

4.2 , interest points are local features with high information content … database contains a set of

models where each model Mk is defined by the vector of invariants Vj calculated at the interest

points of the model images);

feature quantity retention method for extracting and retaining, as a feature quantity, each of the

input image and the model image (see section 1.2, 2, 4.2, 4.4; database contains a set of models,

each model Mk is defined by the vectors of invariants calculated at the interest points of the

model images; during the storage process, each vector is added to the database; during

recognition consists of finding the model which corresponds to a given query image, that is the

model which is most similar to this image, for this image a set of vectors is computed which

corresponds to the extracted interest points and then compared);

feature quantity comparison method for comparing each feature point of the input image with

each feature point of the model image and generating a candidate-associated feature point pair

having similar feature quantities (see section 4.2, 4.2.1, recognition consists of finding the model

Mk which corresponds to a given query image , that is the model which is most similar to this

image .. that produces a sum that is stored in the vector T(k)); and

model attitude estimation method for detecting the presence or absence of the model on the input

image using the candidate-associated feature point pair and estimating a position and an attitude

of the model (see section 4.3 geometric constraint is added based on the angle between neighbor

points based on the transformation that can be locally approximated by a similarity

transformation which increases the score of the object to be recognized by having it be more

distinctive), if any, wherein the feature quantity comparison method itinerantly shifts feature

points to be compared to find distances and generates the candidate-associated feature point pair

by assuming a shortest distance (see section 4.2, 4.2.1, 4.3, 4.4 semilocal constraints are utilized

so there is no miss-detection of points which has the p closest features are selected which

therefore transforms the vector T(k) which is determined by the distance threshold t according to

the X^2 distribution).

It would have been obvious at the time the invention was made to one of ordinary skill in

the art to modify the Watanabe reference to utilize feature point extracting, feature quantity

retention, feature quantity comparison, model attitude estimation as taught by Schmid, in order to

increase the reliability of the robot to track and retrieve targeted objects by improving the

tracking ability of objects even if the image of the targeted object is "take from different

viewpoints" or "only [a] part of [the] image is given" (see section 5.2.2.3, 5.2.2.4).

Roehrig, in the same field of endeavor, teaches extracting and retaining, as a feature

quantity, a density gradient direction histogram at least acquired from density gradient

information in a neighboring region at the feature point, the density gradient direction histogram

storing a number of points near the feature point having each of a plurality of gradient directions

(see col. 1, lines 60-67, col. 2, lines 1-40; central point or region, a histogram of gradient

directions is centered around the candidate point).

It would have been obvious at the time the invention was made to one of ordinary skill in

the art to modify Watanabe with Schmid combination to utilize density gradient direction

histogram and to incorporate the density gradient direction histogram in comparing to candidate-associated feature point pair as taught by Roehrig, to detect and match certain previously stored images or data with high speed, high precision, and high accuracy (see col. 1, lines 40-59).

10.   **Claim 19** is rejected under 35 U.S.C. 103(a) as being unpatentable over Watanabe et al (US 7,084,900 B1), Schmid et al ("Local Grayvalue Invariants for Image Retrieval", IEEE) with Roehrig et al (US 5,815,591), and further in view of Lowe ("Object Recognition from Local Scale-Invariant Features", Computer Vision).

Regarding **claim 19**, Watanabe discloses an autonomous robot apparatus (figure 1, col. 2, lines 37-60, wrist of a robot RB that is included in the robot system) capable of comparing an input image with a model image containing a model to be detected and extracting the model from the input image, the apparatus comprising:

image input means for imaging an outside environment to generate the input image (figure 1, numeral 20; col. 2, lines 37-60, image capturing device (camera or visual sensor) that captures an image of a stack of workpieces); and a processor (figure 3, numeral 1; col. 3, lines 3-10, robot operation programs that are performed by the processor).

Watanabe does not disclose a feature point extracting method for extracting a feature point from each of the input image and the model image;

feature quantity retention method for extracting and retaining a feature quantity in a neighboring region at the feature point in each of the input image and the model image, the feature quantity being a density gradient direction histogram storing a number of points near the feature point having each of a plurality of gradient directions;

feature quantity comparison method for comparing the feature quantity of each feature

point of the input image with the feature quantity of each feature point of the model image and

generating a candidate-associated feature point pair having similar feature quantities; and

a model attitude estimation method for detecting the presence or absence of the model on the

input image using the candidate-associated feature point pair and estimating a position and an

attitude of the model, if any, wherein the model attitude estimation means repeatedly projects an

affine transformation parameter determined from three randomly selected candidate-associated

feature point pairs onto a parameter space and finds an affine transformation parameter to

determine a position and an attitude of the model based on an affine transformation parameter

belonging to a cluster having the largest number of members out of clusters formed on a

parameter space.

Schmid, in the same field of endeavor, teaches a feature point extracting method for

extracting a feature point from each of the input image and the model image (see section 1.2, 2,

4.2, 4.4; database contains a set of models, each model Mk is defined by the vectors of invariants

calculated at the interest points of the model images; during the storage process, each vector is

added to the database; during recognition consists of finding the model which corresponds to a

given query image, that is the model which is most similar to this image, for this image a set of

vectors is computed which corresponds to the extracted interest points and then compared);

feature quantity retention method for extracting and retaining each of the input image and the

model image (see section 1.2, 2, 4.2, 4.4; database contains a set of models, each model Mk is

defined by the vectors of invariants calculated at the interest points of the model images; during

the storage process, each vector is added to the database; during recognition consists of finding

the model which corresponds to a given query image, that is the model which is most similar to this image, for this image a set of vectors is computed which corresponds to the extracted interest points and then compared);

feature quantity comparison method for comparing the feature quantity of each feature point of the input image with the feature quantity of each feature point of the model image and generating a candidate-associated feature point pair having similar feature quantities (see section 4.2, 4.2.1, recognition consists of finding the model Mk which corresponds to a given query image , that is the model which is most similar to this image .. that produces a sum that is stored in the vector T(k)); and

model attitude estimation method for detecting the presence or absence of the model on the input image using the candidate-associated feature point pair and estimating a position and an attitude of the model (see section 4.3 geometric constraint is added based on the angle between neighbor points based on the transformation that can be locally approximated by a similarity transformation which increases the score of the object to be recognized by having it be more distinctive).

It would have been obvious at the time the invention was made to one of ordinary skill in the art to modify the Watanabe reference to utilize feature point extracting, feature quantity retention, feature quantity comparison, model attitude estimation as taught by Schmid, in order to increase the reliability of the robot to track and retrieve targeted objects by improving the tracking ability of objects even if the image of the targeted object is "take from different viewpoints" or "only [a] part of [the] image is given" (see section 5.2.2.3, 5.2.2.4).

Roehrig, in the same field of endeavor, teaches extracting and retaining as a feature

quantity in a neighboring region at the feature point, the feature quantity being a density gradient

direction histogram storing a number of points near the feature point having each of a plurality of

gradient directions (see col. 1, lines 60-67, col. 2, lines 1-40; central point or region, a histogram

of gradient directions is centered around the candidate point).

It would have been obvious at the time the invention was made to one of ordinary skill in

the art to modify Watanabe with Schmid combination to utilize density gradient direction

histogram and to incorporate the density gradient direction histogram in comparing to candidate-

associated feature point pair as taught by Roehrig, to detect and match certain previously stored

images or data with high speed, high precision, and high accuracy (see col. 1, lines 40-59).

Lowe teaches projecting an affine transformation parameter determined from three

randomly selected candidate-associated feature point pairs onto a parameter space (see section 1

scale-invariant features are efficiently identified by using a staged filter approach .. the features

achieve partial invariance to local variations using affine or 3D projections by blurring the image

gradient locations .. when at least 3 keys agree on the model parameters with low residual) and

finds an affine transformation parameter to determine a position and an attitude of the model

based on an affine transformation parameter belonging to a cluster having the largest number of

members out of clusters formed on a parameter space (see sections 3, 6, 9 solve for the affine

transformation parameters … select key locations at maxima and minima of a difference of

Gaussian function applied in scale space).

It would have been obvious at the time the invention was made to one of ordinary skill in

the art to modify Watanabe, Schmid, with Roehrig combination to utilize affine transformation

parameter as taught by Lowe, to "allow for more accurate verification and pose determination than in approaches that rely only on indexing" (see section 9).

Response to Arguments

11.   Applicant's arguments with respect to **claim 16** have been considered but are moot in view of the new ground(s) of rejection.

Furthermore, applicant argues that the "extracting and retaining, as a feature quantity, a density gradient direction histogram" is not disclosed as amended in **claim 16** (see pg. 18, first paragraph). This argument is not considered persuasive since section 1.2, 2, 4.2, 4.4; database contains a set of models, each model Mk is defined by the vectors of invariants calculated at the interest points of the model images; during the storage process, each vector is added to the database; during recognition consists of finding the model which corresponds to a given query image, that is the model which is most similar to this image, for this image a set of vectors is computed which corresponds to the extracted interest points and then compared. The reference meets the limitation of the extracting and retaining, as a feature quantity. Furthermore, the arguments for claim 16 are irrelevant since the structure of the rejection has been changed due to the addition of the newly added limitation expressly defining a density gradient direction histogram.

Applicant's arguments with respect to **claim 1** have been considered but are moot in view of the new ground(s) of rejection.

Furthermore, applicant argues that the "feature quantity retention means" is not disclosed as amended in **claim 1** (see pg. 18, fourth paragraph). This argument is not considered persuasive since section 1.2, 2, 4.2, 4.4; database contains a set of models, each model Mk is defined by the vectors of invariants calculated at the interest points of the model images; during the storage process, each vector is added to the database; during recognition consists of finding the model which corresponds to a given query image, that is the model which is most similar to this image, for this image a set of vectors is computed which corresponds to the extracted interest points and then compared. The reference meets the limitation of the claim and furthermore, the arguments for claim 1 are irrelevant since the structure of the rejection has been changed due to the addition of the newly added limitation expressly defining a density gradient direction histogram.

Regarding **claims 2-10**, applicant argues that the claims are allowable due to the same reasons as mentioned in claim 1 and the dependency from claim 1 (see pg. 18, fourth, fifth paragraph, pg. 19, first paragraph). This reason is not considered persuasive since claim 1 stands rejection under a new ground(s) of rejection.

Applicant's arguments with respect to **claim 11** have been considered but are moot in view of the new ground(s) of rejection.

Furthermore, applicant argues that the "feature quantity retention means" is not disclosed as amended in **claim 11** (see pg. 19, fourth paragraph). This argument is not considered persuasive since section 1.2, 2, 4.2, 4.4; database contains a set of models, each model Mk is defined by the vectors of invariants calculated at the interest points of the model images; during the storage process, each vector is added to the database; during recognition consists of finding

the model which corresponds to a given query image, that is the model which is most similar to this image, for this image a set of vectors is computed which corresponds to the extracted interest points and then compared. The reference meets the limitation of the claim and furthermore, the arguments for claim 11 are irrelevant since the structure of the rejection has been changed due to the addition of the newly added limitation expressly defining a density gradient direction histogram.

Regarding **claims 12-15**, applicant argues that the claims are allowable due to the same reasons as mentioned in claim 11 and the dependency from claim 11 (see pg. 19, fourth paragraph). This reason is not considered persuasive since claim 11 stands rejection under a new ground(s) of rejection.

Applicant's arguments with respect to **claim 17** have been considered but are moot in view of the new ground(s) of rejection.

Furthermore, applicant argues that the "extracting and retaining" is not disclosed as amended in **claim 17** (see pg. 20, second paragraph). This argument is not considered persuasive since section 1.2, 2, 4.2, 4.4; database contains a set of models, each model Mk is defined by the vectors of invariants calculated at the interest points of the model images; during the storage process, each vector is added to the database; during recognition consists of finding the model which corresponds to a given query image, that is the model which is most similar to this image, for this image a set of vectors is computed which corresponds to the extracted interest points and then compared. The reference meets the limitation of the claim and furthermore, the arguments for claim 17 are irrelevant since the structure of the rejection has been changed due to the addition of the newly added limitation expressly defining a density gradient direction histogram.

Applicant's arguments with respect to **claim 18** have been considered but are moot in view of the new ground(s) of rejection.

Furthermore, applicant argues that the "feature quantity retention means" is not disclosed as amended in **claim 18** (see pg. 20, last paragraph). This argument is not considered persuasive since section 1.2, 2, 4.2, 4.4; database contains a set of models, each model Mk is defined by the vectors of invariants calculated at the interest points of the model images; during the storage process, each vector is added to the database; during recognition consists of finding the model which corresponds to a given query image, that is the model which is most similar to this image, for this image a set of vectors is computed which corresponds to the extracted interest points and then compared. The reference meets the limitation of the claim and furthermore, the arguments for claim 18 are irrelevant since the structure of the rejection has been changed due to the addition of the newly added limitation expressly defining a density gradient direction histogram.

Applicant's arguments with respect to **claim 19** have been considered but are moot in view of the new ground(s) of rejection.

Furthermore, applicant argues that the "feature quantity retention means" is not disclosed as amended in **claim 19** (see pg. 21, fourth paragraph). This argument is not considered persuasive since section 1.2, 2, 4.2, 4.4; database contains a set of models, each model Mk is defined by the vectors of invariants calculated at the interest points of the model images; during the storage process, each vector is added to the database; during recognition consists of finding the model which corresponds to a given query image, that is the model which is most similar to this image, for this image a set of vectors is computed which corresponds to the extracted interest points and then compared. The reference meets the limitation of the claim and furthermore, the

arguments for claim 19 are irrelevant since the structure of the rejection has been changed due to

the addition of the newly added limitation expressly defining a density gradient direction

histogram.

Conclusion

12.   Applicant's amendment necessitated the new ground(s) of rejection presented in this

Office action. Accordingly, **THIS ACTION IS MADE FINAL**. See MPEP § 706.07(a).

Applicant is reminded of the extension of time policy as set forth in 37 CFR 1.136(a).

A shortened statutory period for reply to this final action is set to expire THREE

MONTHS from the mailing date of this action. In the event a first reply is filed within TWO

MONTHS of the mailing date of this final action and the advisory action is not mailed until after

the end of the THREE-MONTH shortened statutory period, then the shortened statutory period

will expire on the date the advisory action is mailed, and any extension fee pursuant to 37

CFR 1.136(a) will be calculated from the mailing date of the advisory action. In no event,

however, will the statutory period for reply expire later than SIX MONTHS from the date of this

final action.

Any inquiry concerning this communication or earlier communications from the

examiner should be directed to EDWARD PARK whose telephone number is (571)270-1576.

The examiner can normally be reached on M-F 10:30 - 20:00, (EST).

If attempts to reach the examiner by telephone are unsuccessful, the examiner's

supervisor, Vikkram Bali can be reached on (571) 272-7415. The fax phone number for the

organization where this application or proceeding is assigned is 571-273-8300.

Information regarding the status of an application may be obtained from the Patent

Application Information Retrieval (PAIR) system. Status information for published applications

may be obtained from either Private PAIR or Public PAIR. Status information for unpublished

applications is available through Private PAIR only. For more information about the PAIR

system, see http://pair-direct.uspto.gov. Should you have questions on access to the Private PAIR

system, contact the Electronic Business Center (EBC) at 866-217-9197 (toll-free). If you would

like assistance from a USPTO Customer Service Representative or access to the automated

information system, call 800-786-9199 (IN USA OR CANADA) or 571-272-1000.

Edward Park
Examiner
Art Unit 2624

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/Vikkram Bali/
Supervisory Patent Examiner, Art Unit 2624